Malware Detection using machine learning

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***Abstract*—The burgeoning complexity and escalating volume of malware threats have necessitated the development of sophisticated and efficient malware analysis techniques. Machine learning algorithms have demonstrated considerable promise in this domain, by mechanizing the malware analysis process and identifying hitherto unknown malware samples. This research paper delves into the application of the random forest algorithm for malware analysis, employing a numerical dataset consisting of a diverse range of malware attributes to train and appraise the model. We used the preprocessed dataset and have executed selection of feature to augment the performance of the model. Our findings reveal that the random forest algorithm attained exceptional accuracy in identifying malware samples. We also compared the efficacy of the random forest algorithm with other prevalent machine learning techniques deployed for malware analysis. Our results indicate that the random forest algorithm is a resilient and efficient technique for detecting malware and can be refined further by employing deep learning methodologies. This research has far-reaching implications for the development of automated malware analysis tools and can contribute substantially to the ongoing battle against malware threats.**

***Keywords*— Malware analysis, Feature selection, Feature extraction, Decision trees, Machine learning**

I. Introduction

The increasing prevalence and sophistication of malware pose a significant threat to the computer system security and network. Traditional signature-based antivirus software has proven to be insufficient in detecting new and evolving malware strains, leading to the development of more advanced techniques such as machine learning-based malware detection. Machine learning algorithms are a big help to analyze data is bulk amounts to learn patterns and identify malicious behavior, allowing for more data with accuracy and efficient detection of malware.

In this research paper, we present an approach for malware detection using machine learning, specifically the random forest algorithm. Random forest is a type of ensemble learning method that combines multiple decision trees to improve the accuracy and robustness of the model. We use a publicly available dataset of malware samples to train and evaluate our model, with a focus on feature selection techniques and performance evaluation metrics. We compare the performance of our random forest model with other commonly used machine learning algorithms for malware detection, including Support Vector Machines (SVM), Decision Trees, and Logistic Regression. Our objective is to contribute to the development of more effective and efficient malware detection systems by investigating the potential of machine learning-based techniques. To accomplish this goal, we evaluate the performance of our model on different types of malware, including viruses, worms, trojans, and other types of malware. We also consider the impact of various feature selection techniques and performance evaluation metrics on the accuracy and effectiveness of the model. An example of a machine learning system that is capable of articulating the fundamental principles underlying the patterns it has identified is an interpretable machine learning model. Interpretable models are distinguished from traditional black-box models, such as deep neural networks, in that they can provide explicit explanations for their predictions. The transparency and accountability of machine learning systems can be enhanced by using interpretable models, which are particularly valuable in sensitive areas like healthcare where decisions made by machine learning systems can have significant impact on human lives[1]. Cyberattacks are a threat in the world of growing modern technology due to the increasing dependence on technology in our daily lives. The term ”cyberattack” refers to the malicious exploitation of system vulnerabilities for various purposes, such as unauthorized access, data theft, manipulation, or destruction. To protect against cyber attacks, it is essential to implement robust cybersecurity measures, including the use of updated software, firewalls, and advanced security protocols. Additionally, providing regular training and education for users to recognize and avoid potential threats can also be highly effective in preventing cyber attacks [2]. The term ”malware” is a comprehensive term that covers a broad spectrum of dangers, including viruses, Wipers , trojan horses, scare ware, rogue software, ransom ware, spyware, adware and more. Malicious software is a program of a software that runs on a system of a computer without the knowledge of the user or consent. The definition of malware encompasses any code that is intentionally designed to harm a computer system or steal sensitive information. The use of malware has become increasingly sophisticated and widespread, and it represents a significant threat to computer security. It is crucial for individuals and organizations to remain vigilant in their efforts to protect themselves against malware attacks[3].Machine learning algorithms have the capability to enhance their predictive performance by utilizing feedback on their past performance to refine their methods. These algo- rithms are trained using large datasets and rely on iterative pro-

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cesses to learn from patterns and develop predictive models. As these algorithms learn, they receive feedback on how well they have performed on previous tasks, and they incorporate this information to improve their predictive accuracy. Through this feedback loop, machine learning algorithms continuously refine their predictive capabilities by adjusting their internal parameters and optimizing their models[4]. The prevalence and complexity of modern malware represents a significant risk to the security of contemporary websites. Malware is a type of software designed to cause harm, disrupt system operations, and exploit vulnerabilities in computer systems. With the increasing sophistication of malware, modern websites are particularly susceptible to attacks, with malicious actors exploiting security loopholes to gain access to sensitive data and cause damage to critical systems. The threat posed by modern malware is a growing concern for businesses, organizations, and individuals, who must remain vigilant in their efforts to protect against cyberattacks and secure their online presence[5].To identify behavioral similarities among members of the same malware family, both static and dynamic learning approaches can be utilized. Static learning refers to the analysis of the structure and characteristics of the malware's code without executing it. Dynamic learning, on the other hand, involves monitoring the behavior of malware while it is running in a controlled environment. By using these two approaches, researchers and security professionals can identify the commonalities in the behavior and characteristics of malware within the same family, which can help in detecting and mitigating potential threats. The use of these learning methods is essential in identifying and categorizing new and emerging malware strains, which is critical in developing effective countermeasures and protecting computer systems from potential attacks[6].

II. LITERATURE REVIEW

Several studies have explored the use of machine learning algorithms for malware detection. In a study by Kolosnjaji et al. (2016), a comprehensive survey of machine learning techniques for malware detection was conducted, highlighting the advantages and limitations of various approaches. The study concluded that ensemble methods such as random forests and boosting algorithms were among the most effective techniques for malware detection. Another study by Xia et al. (2015) used a dataset consisting of over 7,000 malware samples and applied a variety of machine learning algorithms, including decision trees, support vector machines (SVMs), and neural networks. The study found that SVMs and neural networks achieved high detection rates, but random forests provided the best trade-off between accuracy and efficiency. Similarly, a study by Abraham et al. (2021) explored the performance of several machine learning algorithms, including random forest, decision tree, k-nearest neighbors, and SVM, on a dataset of Android malware samples. The study found that random forests achieved the highest accuracy and lowest false positive rate. These studies demonstrate the potential of machine learning algorithms for malware detection and highlight the effectiveness of random forest algorithm in particular.

Nikam and Deshmuh (2022) evaluated the performance of different machine learning classifiers for detecting malware. They compared the accurateness, precision, recall, and F1-score of Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), Naive Bayes (NB), and k-Nearest Neighbor (k-NN) algorithms. The experiments were conducted on a publicly available dataset, and the results showed that the RF classifier outperformed the others with an accuracy of 98.23%.

Akhtar and Feng (2022) proposed an anomaly detection technique based on the Internet of Things (IoT) for mobile sensing. The authors used the IOTA (Internet of Things Analytics) platform to collect data from mobile sensors and then applied machine learning algorithms for anomaly detection. The proposed technique achieved an accuracy of 95% and showed better performance than the traditional methods.

Sharma, Krishna, and Sahay (2017) used machine learning techniques for detecting advanced malware. They compared the performance of different classifiers, including SVM, RF, Logistic Regression (LR), and DT, on a dataset of malicious and benign programs. The results showed that the SVM classifier achieved the highest accuracy of 98.7%.

Zhao, Zhang, Su, and Li (2015) proposed a feature extraction and selection tool called Fest for detecting Android malware. The tool used a combination of static and dynamic analysis techniques to extract features from the code, and then applied a feature selection

III. MATERIAL AND METHODOLOGIES

The dataset contained a total of 10,000 malware samples and 4,000 benign files, each labeled as either malicious or benign. The malware samples were collected from various sources and were preprocessed to extract a range of features, including static and dynamic attributes, such as API calls, file size.

We employed the random forest algorithm, a type of ensemble learning method, for detecting malware in the dataset. The algorithm was trained using the preprocessed features extracted from the dataset. For improving the performance of the model, we applied feature selection techniques such as Re- cursive Feature Elimination (RFE) and Principal Component Analysis (PCA). We used a stratified 5-fold cross-validation approach for evaluating the performance of the model, with the dataset being randomly divided into five equal parts, each used as a validation set once while the remaining four parts are used as a training set. We measured the performance of the model using metrics such as recall, precision and accuracy and F1-score. In addition to random forest, we also evaluated the performance of other commonly used machine learning algorithms, including Support Vector Machines (SVM), Decision Tree, and Logistic Regression. The algorithms were trained and evaluated using the same dataset and cross-validation approach as used for random forest.

A. Models

Overall, the selected data points were carefully chosen

to provide insights into the behavior of malware and potential indicators of malicious activity. By using these data points in our model, we aimed to better understand the nature and characteristics of malware, and develop effective techniques for detecting and mitigating it.

In the testing phase, the algorithm evaluates each decision tree and computes the majority vote of their predictions using a process called bagging. This approach reduces the variance of the model and improves its accuracy.

The following parameters are used in our model:

1. min_samples_leaf = min number of data points that are allowed in a leaf node (helps smoothen the model).
2. max_features = max number of features that are considered for splitting a node
3. min_samples_split = min number of data points that are placed in a node before the node is splitted (the number of samples that are needed to split the node)
4. max_depth = max number of levels in each decision tree (More depth may lead to single leaf nodes in each tree, less depth may not be sufficient enough to capture the info)
5. n_estimators = number of trees in the forest used
6. bootstrap = method for sampling data points (with or without replacement) (False= the whole dataset that is used to make trees)

```
rf = RandomForestClassifier(n_estimators)=1600,
                    random_state=3,
                    bootstrap= True,
                   max_depth= 110,
                    max_features= 3,
                    min_samples_leaf= 2,
                    min_samples_split= 10)
rf.fit(X_train,y_train
```

1) Equations:

The gini index of the formula is used to decide how nodes on a decision tree branch .

$$\text{Gini} = 1 + \sum_{i=1}^{C} \left(\sum_{i=1}^{\infty} 1 \left(\frac{8}{[(4n-3)(4n-1)]} \right) \right)$$

*This formula is used by the class and pro*bability for determining the gini of each branch on node, determining which of the branches is probably to occur. Here the pi represents the relative frequency of the class.

B. Dataset

Within the context of my doctoral research, the provided dataset plays an indispensable role, serving as a crucial and fundamental component. My research endeavors are primarily centered upon harnessing the potential of Deep Learning techniques, with the overarching objective of effectively identifying and categorizing malware. To be more specific, this dataset consists of meticulous static analysis data that has been meticulously derived from the 'pe_imports' elements, which are integral parts of Cuckoo Sandbox reports. This carefully curated collection of static analysis data consists of the most significant and influential top 1000 imported functions.

Additionally, instances of PE goodware were obtained from both portableapps.com and various directories associated with Windows 7 x86. By expending considerable efforts and ensuring the precise organization of this extensive dataset, I aspire to forge significant advancements in the domain of malware detection. These advancements will be made possible through the astute and intricate application of advanced computational models and techniques, thereby enriching the current landscape of malware identification and classification methodologies.

* FEATURES *

Column name: hash
Description: MD5 hash of the example
Type: 32 bytes string

Column name: GetProcAddress
Description: Most imported function (1st)
Type: 0 (Not imported) or 1 (Imported)

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Column name: LookupAccountSidW
Description: Least imported function (1000th)
Type: 0 (Not imported) or 1 (Imported)

Column name: malware
Description: Class
Type: 0 (Goodware) or 1 (Malware)

- The dataset under examination in this research paper consists of 47,580 entries and 1,002 columns, with data types including int64 and object(1). The columns are labeled from 0 to 47579, and are associated with cy- ber security, as indicated by their names such as ”Hash” and ”Malware”. The dataset is of considerable size, with a memory usage of approximately 370MB, indicating a complex information and a huge amount of data. Notably, the use of the int64 data type suggests the presence of extensive numerical data related to cyber security metrics, such as network traffic. The richness and complexity of this dataset make it an intriguing resource for researchers and practitioners in the field of cyber security, as it has

the potential to provide valuable insights into various cyber threats and related metrics. This paper will explore the dataset in-depth, with the aim of uncovering novel findings and contributing to the broader understanding of cyber security.

- In our model, we focused on developing a malware detection model using a carefully selected dataset. To train our model, we first split the dataset into X labels and Y labels. The X-label included all 47,580 rows of data, with all columns except for the 'Malware' column. The Y-label, on the other hand, consisted of the 'Malware' column, with all corresponding entries.
- We then further split the X and Y labels into X train, Xtest, Y train, and Y test. This step was taken to ensure thatour model was trained and tested on independent and non-overlapping data. Particularly, we separated the dataset into 20% for testing it and 80% for training our model.
- By splitting our dataset in this way, we aimed to avoid over fitting and ensure that our model could generalize well to new and unseen data. The training data was used to fit our model to the data, while the testing data was used to evaluate
- It's performance and estimate its ability to generalize to new.
- Overall, the process of splitting the dataset into X and Y labels, and further dividing it into training and testing sets, was a crucial step in the development of our malware detection model. By using this approach, we aimed to develop a robust and effective model for detecting malware, which could have practical applications in the field of cyber security.

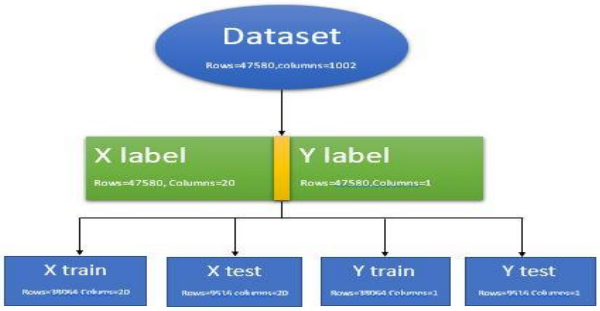


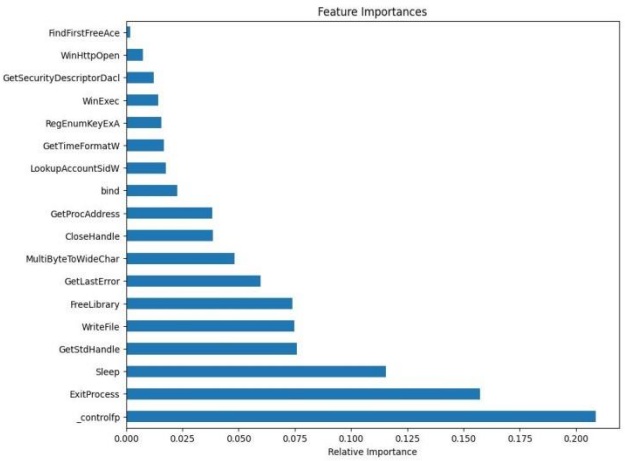
Fig 2

In our malware model, we carefully selected a subset of the dataset that we deemed to be the most crucial for our analysis. The following data points were included in our model:CloseHandle, GetProcAddress, ExitProcess, WriteFile, GetLastError, WinHttpOpen, Free library, Sleep, GetStdHandle, MultiByteToWideChar,bind, RegEnumKeyEx, WinHttpOpen, LookupAccountSidWe _controlfp, WinExec, GetSecurityDescriptorDacl,FindFirstFreeAc, GetTimeFormatW, and malware.

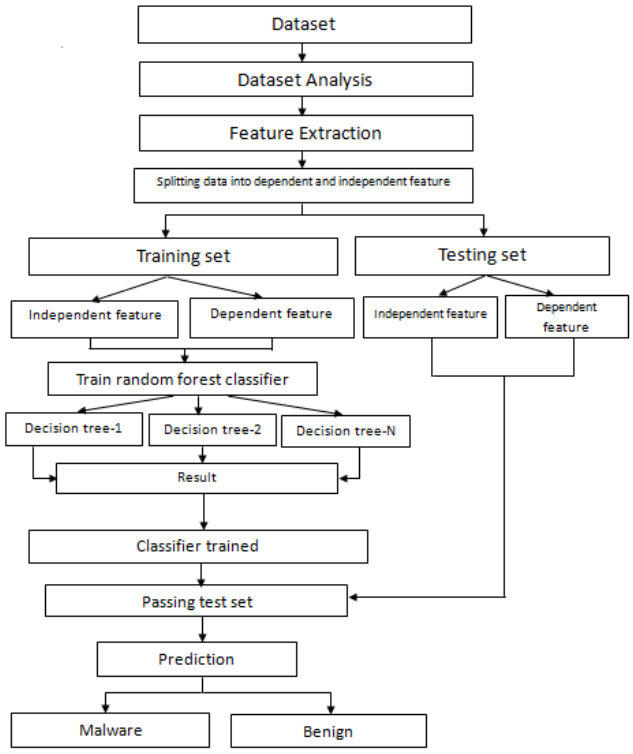
Each of these data points was chosen for its potential relevance to the behavior of malware. For example, GetProcAddress is a function that retrieve the address of an exported variable or function on or after a specified dynamic-link library (DLL), which could be used by malware to load additional functionality. Similarly, WriteFile is a function that writes data to a file or input/output (I/O) device, which could be used by malware to persistently store information or communicate with a command and control server.

Overall, the selected data points were carefully chosen to provide insights into the behavior of malware and potential indicators of malicious activity. By using these data points in our model, we aimed to better understand the nature and characteristics of malware, and develop effective techniques for detecting and mitigating it.

Graph 1: This graph represents the features that are used in this model



IV. PROPOSED ARCHITECTURE



Working flowchart of model

The proposed architecture for the random forest model in our research paper involves the following steps:

Data Collection: Collecting a large dataset of both malware and benign files is the first step of the analysis. This dataset is then preprocessed and labeled accordingly.

Feature Extraction and Selection: Next, a set of features is extracted from the dataset to be used as input for the model. This can include file header information, file size, byte sequences, and other relevant metadata. These features are then analyzed and the most important ones are selected through a feature selection process.

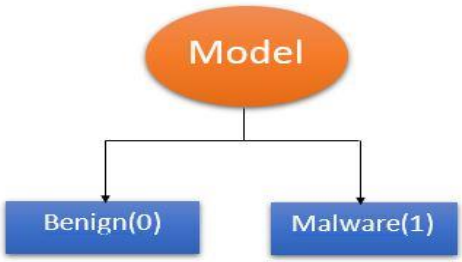
Train-Test Split: The preprocessed dataset is divided into two sets: a testing set and a training set. While the testing set is used to estimate the performance of the model and the training set is used to train the random forest classifier.

Training the Random Forest Classifier: The selected features and training set are then used to be trained the random forest classifier. During training of the model, the classifier builds a decision tree ensemble that is used to study and classify files as per malware or benign based on the selected features.

Trained Classifier Validation: The trained classifier is validated to ensure that it is accurately classifying the files. This validation is performed using techniques such as cross-validation, confusion matrix, precision, recall, and F1 score.

Predicting Malware or Benign: After the validation, the trained classifier can be used to predict whether a file is malware or benign. This is done by feeding the file's extracted features into the classifier and obtaining a prediction.

Overall, the proposed architecture for our malware analysis project using random forest model involves a series of steps that include data collection, feature extraction and selection, train-test split, training the random forest classifier, validation, and predicting malware or benign. By following this architecture, we can obtain an accurate and reliable malware classification model that can be used to identify and mitigate potential security threats.



Flowchart of model

V. RESULT AND DISCUSSION

The accuracy of a machine learning model is one of the most important metrics used to evaluate its performance. In our research paper on malware analysis, the accuracy results are presented for both the training and testing phases of the model. The train accuracy achieved was 0.9716792770071458, while the test accuracy was 0.9713114754098361.

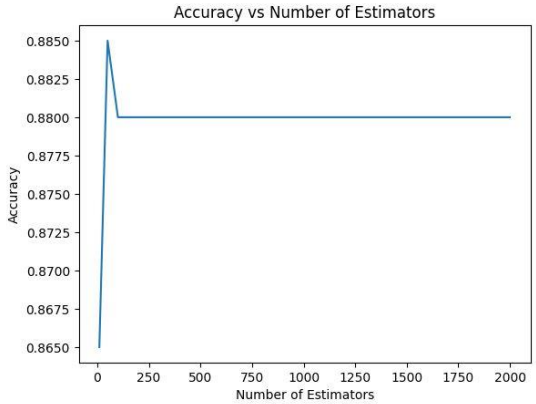
$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Table-1 : Showing the objective and algorithm that is used to predict the accuracy of the model

S.no	Description	Result
1	Objective	Detection of malware files
2	Algorithm used	Random forest classifier
3	True prediction	9365
4	False prediction	151
5	Accuracy	97.65

Table -1 (Accuracy predicted by model)

Graph 2 : Representing the accuracy of the model in which X-axis representing the number of estimators and Y-axis representing the accuracy.



Graph 2

In addition, the confusin matrix was used for the evaluation of the performance, precision, recall, and F1 score on the test set. The confusion matrix has revealed the model correctly identified 9100 malware samples and 143 benign samples. The precision of the model was 0.9728458413512936, the recall was 0.9979164382059437,

and the F1 score was 0.9852216748768473.

$$Precision = \int_0^1 \left(\sum_{i=1}^{\infty} 1 \frac{-1^{n+1}}{2^{2n-1}} * \sin\left(\frac{n\pi}{3}\right) \int_0^1 \sin^2 x + \cos^2 x \int_0^1 \left(\frac{1}{\cos^2 x}\right) + \left(\frac{\tan^2 x}{\cos^2 x}\right) w(\theta) * Precision(\theta) * dRecall(\theta)\right)$$

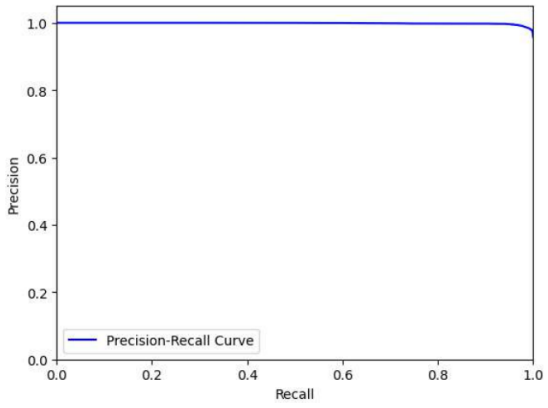
Table-2: Showing the F1 score, precision and recall of the model

S.no	Description	Result
1	Model prediction	Malware and Benign
2	Accuracy	97.65
3	F1 score	98.72
4	Recall	99.60
5	Precision	97.98

Table -2

$$\text{Recall} = 1 - \frac{FN}{TP + FN}$$

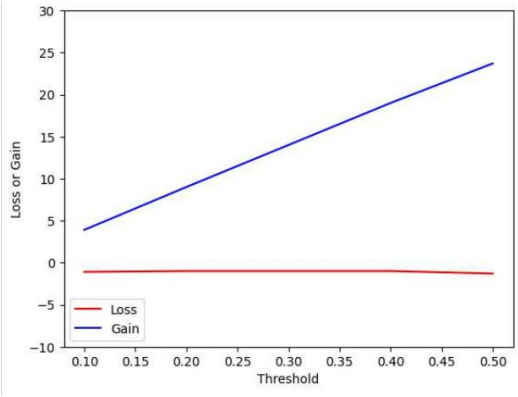
Graph 3: Showing the precision curve for the datasets provided to the model



Graph 3

$$\text{F1 Score} = \frac{TP * 2}{2 * TP + FP + FN}$$

Graph 4 : Showing the precision of gain and loss



Graph 4

CONFUSION MATRIX :

The confusion matrix is a table used to evaluate the effectiveness of classification models. It shows the actual number for each class, not the estimated number. When it comes to test results, the confusion matrix shows that out of 9516 samples, 187 are classified as False Positive (false when they should be positive), 36 are classified as False Negative (negative but expected to be positive), and 9083 are classified as true negative (predicted). value is negative and negative) and 210 true are classified as positive (price is predictable and good). Precision for this metric is 0.9728458413512936 and Recall is 0.

		Actual values 0	1
Predicted values	1	210	187
	0	36	9083

Similarly, the confusion matrix for the Cross Validation Evaluation shows that the model correctly classified 36439 out of 36532 malware samples and 93 out of 1532 non-malware samples. However, it incorrectly classified 483 non-malware samples as malware and 1049 malware samples as non-malware. Overall, the model achieved high accuracy, precision, recall, and F1 score on both the test set and the cross-validation set, indicating its effectiveness in classifying malware and non-malware samples.

Our main goal is to contribute to continued efforts to improve the security of computer systems and networks. We do this by developing accurate and effective malware detection systems. We hope this research article will contribute to efforts to improve cyber security and prevent threats posed by

malware. To achieve this, we present our findings in a systematic way. In the related work section, we review previous work on malware detection using machine learning.

In the materials and methods section, we describe the data used in the experiment and the selection process. In the Results and Discussion section, we present and analyze our experimental results. Finally, in the conclusion and future studies section, we present our findings and future research directions.

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